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Alzheimer's disease detection from optimal electroencephalogram channels and tunable Q-wavelet transform

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ABSTRACT

Alzheimer's disease (AD) is a non-curable neuro-degenerative disorder that has no cure to date. However, it can be delayed through daily activity assessment using a robust electroencephalogram (EEG) based system at an early stage. A selection technique using a Shannon entropy to signal energy ratio is proposed to select optimal EEG channels for AD detection. A threshold for channel selection is calculated using the best detection accuracy during backward elimination. The selected EEG channels are decomposed using tunable Q-wavelet transform (TQWT) into nine different subbands (SBs). Four features: Katz's fractal dimension, Tsallis entropy, Relyi's entropy, and kurtosis are extracted for each SB. These features are used to train and test support vector machine, k-nearest neighbor, ensemble bagged tree (EBT), decision tree, and neural network for detecting AD patients from normal subjects. 16-channel EEG signals from 12 AD and 11 normal subjects recorded using the 10-20 electrode placement method are used for evaluation. Ten optimized channels are selected, resulting in 32.5% compression. The experimental results of the proposed method showed promising classification accuracy of 96.20% with the seventh SB features and EBT classifier. The significance of these features was inspected by using the Kruskal-Wallis test.

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1. INTRODUCTION

In recent years, human life expectancy has increased due to the constant development of medical health care systems. In the UK, life expectancy is increased to 79 and 83 years for male and female respectively [1]. However, this leads to getting more neurological disorders that can have adverse effects on the daily routine of human beings. Though developed countries explore human brain, the Alzheimer's disease (AD) is still a non-curable neuro-degenerative disorder. If AD is left without proper treatment, it can lead to the death of AD patient. Almost 20-25% people of age more than 65 years suffer from mild cognitive impairment (MCI). For every three seconds, someone develops dementia somewhere in the world. It is reported that almost 50 million people have dementia in the year 2020. This AD rate is rising to double every 20 years, it will reach

80 million in 2030 and 150 million in 2050 [2]. AD is caused due to spread of brain cell loss, senile plaques, and neurofibrillary tangles. As the progression of AD, the cognitive deficits like judgment, planning etc will be observed in the AD patients [3]. Thence, it is desire to develop a robust method to detect AD at an early stage. The AD shown predominant abnormalities in electroencephalogram (EEG) such as reduction in complexity, slowing, and perturbations in synchrony. In earlier reported work, the EEG has shown promising results for other neurological disorders like motor imagery, sleep stages, seizure, and alcoholism detection [4] because of its high temporal resolution, portability and non-invasive nature [5].

In earlier reported work, EEG-based different entropy algorithms have been introduced to detect AD such as approximate entropy (ApEn) [6], spectral entropy (SpEn), sample entropy (SampEn) [7], multiscale entropy (MSE) [8], auto mutual information (AMI) [9], quadratic sample entropy (QSE) [10], and fuzzy entropy (FuzzyEn). It was found that the ApEn, SampEn, SpEn, and FuzzyEn values are lower in AD patients' EEG than NC [11]. Abásolo *et al.* [9] utilized AMI and ApEn features to detect AD and reported 90.91% of maximum classification accuracy. However, these entropies are biased estimators and very sensitive to parameter value. For instance, Fiscon *et al.* [12] used both fast Fourier transform (FFT) and wavelet domain features with decision tree (DT) and reached upto 93% classification rate. Despite having an EEG dataset of AD, MCI, and normal controlled (NC) subjects, they performed only binary classification. Burcu *et al.* [13] has developed an efficient technique to detect AD from NC. Authors used power spectral density (PSD) and coherence-based features with support vector machine (SVM) and k-nearest neighbor (KNN) classifiers. Consequently, obtained an accuracy of 93% and 94% for SVM and KNN respectively. In a recent study, [14] utilized empirical mode decomposition (EMD) and wavelet-based Hjorth parameters (HP) with SVM and KNN to detect the AD from NC subjects. They achieved 95.79% of accuracy using SVM.

Sharma *et al.* in [15], evaluated the parameters PSD, crest factor, fractal dimension, kurtosis, skewness, and entropy from AD and NC EEG signals. The SVM and artificial neural network have trained and tested using these parameters with a 10-fold cross-validation technique and reached to 89% accuracy. Similarly, Durongbhan *et al.* in [16], investigated the frequency and time-frequency based features to detect AD. The results obtained from the this method demonstrated that the classification accuracy reached up to 93% for FFT and 95% for the wavelet-based feature set by KNN classifier with $k = 2$.

In the above discussed state-of-art techniques are bounded by their performance over many limitations, which are as follows: i) The non-linear features (different types of entropies) fail to capture spectral information of EEG signals as they are used in the time domain; ii) The FFT-based methods suffer from localization problems in time and frequency. Hence, it's difficult to identify significant features from EEG signals; iii) Several studies proposed methods on wavelet-based techniques. However, the selection of the mother wavelet function and number of levels is a tedious task; and iv) On the other hand, the earlier proposed methods have utilized EEG signals captured from all channels. Hence, there is an increase in computational complexity and data redundancy.

We proposed a novel framework for detecting AD patients from NC subjects based on channel optimization and feature extraction from Tunable-Q Wavelet Transform (TQWT) to address these limitations. The main contributions of the proposed technique are as follows: i) The present study proposed a novel method to optimize the number of EEG channels used for the detection of AD patients from NC subjects; ii) To overcome the limitations of FFT and wavelet transform limitations, the TQWT decomposition technique is employed to get the EEG subbands (SBs); iii) Four features, namely, Katz's fractal dimension (KFD), Tsallis entropy (TsEn), Renyi's entropy (ReEn), and kurtosis (K), were extracted from decomposed EEG SBs; iv) The significance of these features has been checked using Kruskal-Walli's (KW) test; and v) Combination of TQWT and different classifiers such as decision tree (DT), SVM, KNN, neural network (NN), and ensemble bagged tree (EBT) have been exploited with a ten-fold cross-validation technique.

2. PROPOSED METHOD

The proposed method consists of four steps: i) channel optimization, ii) TQWT decomposition, iii) feature extraction, and iv) classification. The channel optimization has been done using Shannon entropy to signal energy ratio. In the second step, the EEG signals from selected channels were decomposed using TQWT into nine SBs. Subsequently, four features are extracted for the selected SBs. Finally, these features were employed to train and test set of five different classifiers with a ten-fold cross-validation technique. The proposed method has illustrated in Figure 1.

2.1. EEG dataset

In the present study, the 12-AD and 11-NC subjects were recruited from Alzheimer's Patients' Relatives Association of Valladolid (AFAVA) for the EEG recordings. The 12 AD patients (7-female and 5-male) having age 72.8 ± 8.0 (mean $\pm$ standard deviation (STD)) years. AD patients were gone through the clinical evaluation, including brain scan and physical test with mini-mental state examination (MMSE) to check their cognitive ability. The MMSE score for AD patients is in the range of 13.2 ± 5.92 points (mean$\pm$ STD). On the other hand, 11-NC (4-female and 7-male) age-matched subjects were enrolled for EEG recordings. The ages of NC subjects varied from 72.7 ± 6.2 years (mean $\pm$STD). After clinical and physical evaluation of NC subjects, it was found that they didn't have any present or past neurological disorder. All EEG signals were recorded using 10-20 electrode placement method by study room 2.3.411 EEG system (Oxford instrument) using 16-electrodes namely, F_z, C_z, P_z, O_1, O_2, F_3, F_8, Fp_1, Fp_2, F_4, F_7, C_3, C_4, T_4, T_3, T_6, and T_5 during day time in multiple sessions. EEG signals are captured during the eye-closed and resting state of the subject in order to reduce the artifacts from EEG recordings. The total five seconds EEG signals were sampled at 256 Hz sampling frequency using 12-bit analog to digital converter. All subjects willingly participated in the EEG recording activity and written informed consent was taken from NC subjects and caregivers of demented patients. The local ethical committee approved this process of EEG recording of Hospital Clinic Universitario de Valladolid (CUV) [17]. This EEG data of AD and NC already used in the [17], [18]. All EEG signals recorded using 16 electrodes are used in the proposed study. The typical sample EEG plots for AD patient and NC subject recorded from C_z electrode is shown in Figures 2(a) and (b).

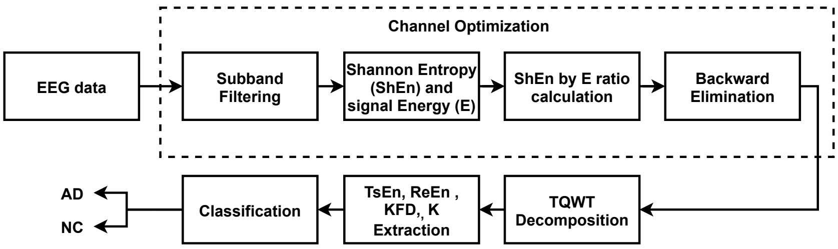

Figure 1. Flow diagram of proposed method

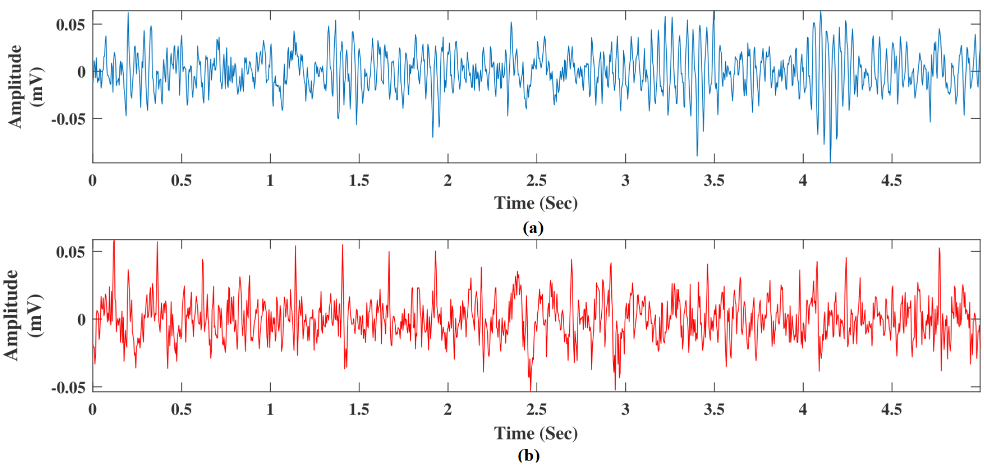

Figure 2. Sample EEG signals of C_z electrode for five second time: (a) AD and (b) NC

2.2. Channel selection method

It is not feasible for any proposed technique to use EEG signals from all the channels. It is desired to develop a method with optimal channel selection to reduce the data redundancy, and computational complexity [19], [20]. EEG signal from each channel is filtered into delta (δ: 0.5-4 Hz), theta (θ: 4-8 Hz), alpha (α: 8-13 Hz), and beta (β: 13-30 Hz) EEG SBs [21]. The channel selection criteria Shannon entropy (ShEn) to signal

energy (E) ratio (SESER) were measured from all EEG SBs from each channel. Afterwords, to remove the redundant EEG channels backward elimination process has been adopted. The SESER is given by (1),

$$SESER = \frac{ShEn}{E} = \frac{-\sum P_m log(P_m)}{\sum s(n)^2} \tag{1}$$

where, P_m are the probabilities of a datum being in bin and $s(n)$ represent samples in EEG data sequence. The signals showing maximum E, minimum ShEn, and minimum SESER value were employed on EEG channels. Out of 16 EEG channels only ten most significant channels (C_z, P_z, O_1, O_2, Fp_1, Fp_2, C_3, T_4, T_3, and T_5) were selected for feature extraction process followed by classification. The Pseudo code for channel optimization have been represented in Algorithm 1.

Algorithm 1 Pseudo code for channel selection algorithm

Filter EEG signal into EEG SBs. Find $ShEn/E$ ratio. Get max(ACC) = TH, channel count $j = 16$;
while ($1 \leq$ i $\leq$ 16) **do**
  Remove C_j
  if $ShEn/E \geq$ TH **then**
    Reject the channel C_i;
    $j \leftarrow j - 1$;
  else
    $j \leftarrow j - 1$, Don't reject C_j
  end if
  $i \leftarrow i + 1$;
end while
The value of j gives the number of optimal channels.

2.3. Tunable Q-wavelet transform (TQWT)

The TQWT is widely used decomposition technique in biomedical signal processing applications. It has the ability to detect the oscillatory and transient components from the signals. TQWT consists of two variable parameters named redundancy (R) and quality factor (Q). Q and R can be changed to get the required time-frequency resolution. The TQWT is consists of a filter bank with two channels, and it can be used iteratively until to get desired time-frequency resolution [22]. The lowpass filter (LPF) can be expressed as:

$$H_0(w) = \begin{cases} 1, & |w| \leq (1-\beta)\pi \\ \Theta(\frac{w+(\beta-1)\pi}{\alpha+\beta-1}), & (1-\beta)\pi < |w| < \alpha\pi \\ 0 & \alpha\pi \leq |w| \leq \pi \end{cases} \tag{2}$$

the expression for high-pass filter (HPF) frequency response is as (3) [22]:

$$H_1(w) = \begin{cases} 0, & |w| \leq (1-\beta)\pi \\ \Theta(\frac{\alpha\pi-w}{\alpha+\beta-1}), & (1-\beta)\pi < |w| < \alpha\pi \\ 1 & \alpha\pi \leq |w| \leq \pi \end{cases} \tag{3}$$

the expression for $\Theta(w)$ shown in above equations is as (4) [22]:

$$\Theta(w) = \frac{1}{2}[cos(w) + 1][2 - cos(w)]^{0.5}, |w| \leq \pi \tag{4}$$

where α and β are the scaling parameters of LPF and HPF in the range of 0 to 1. These parameters should be selected to satisfy $\alpha + \beta > 1$. The Q is depending on the SB central frequency (f_0) and Bandwith B_w and $Q = f_0/B_w$. The α and β can be measured from Q and R using $\beta = 2/(Q+1)$ and $\alpha = 1 - \beta/R$ [22]. In the proposed method we have mentioned that EEG signals from selected channels have been evaluated to detect the AD from NC. In decomposition of EEG signals using TQWT, the selection of the parameters like Q, R, and J is very important. We adopted the systematic search technique for optimization of Q, R, and J parameters. The parameters Q and J were varied in the range 1 to 10. The experimental results showed that at $Q = 1$ and $J = 8$ the proposed method provides the highest accuracy. The Value of R=3 to avoid the unwanted excessive ringing of wavelets while performing the TQWT. Here, to find the discriminant features from EEG signals of AD and NC, we selected $Q = 1, R = 3$, and $J = 8$. Thus, nine different SBs from each raw EEG signal have

been evaluated to detect the AD patient from NC subjects. The frequency response of TQWT for specified values of Q, R, and J has shown in Figure 3.

2.4. Feature extraction

EEG signals are decomposed into nine different SBs using TQWT to extract significant and dominant features. These SBs are used to extract the four features, namely, KFD, TsEn, ReEn, and K. Further to check the significance of the features KW test have been employed on feature vectors. The KW test is non-parametric technique used to check whether samples belongs to same distribution. It has ability to evaluate the two or more independent samples of different or equal sizes [5], [19]. TsEn is used to evaluate the physical behaviour of any system. It is a generalization of ShEn. It can be used in the applications of detecting spikes, bursts, and EEG rhythms. TsEn measure has proved to be more robust compared to ShEn. It can be expressed as [23]:

$$TsEn = \frac{1}{q-1}\left(1 - \sum_{m=1}^{N} p_m(v)^q\right) \tag{5}$$

where, q is parameter which is greater than 0. P_m are the probabilities of a datum being in bin. N is number of samples in EEG. ReEn has been used as feature in many applications of EEG such as epilepsy, drowsiness detection etc. It generalizes the Hartley entropy, collision entropy, ShEn, and the min-entropy. It is utilised to calculate entanglement. It can be expressed as [5]:

$$ReEn = \frac{1}{q-1}\left(log \sum_{m=1}^{N} p_m(v)^q\right) \tag{6}$$

where, q is parameter value between 0 and 1. N is maximum number of segments in EEG signal. The KFD This is one of the most important type of fractal dimensions used to measure the complexity of any non-stationary signals. The KFD can be defined as the sum and average of Euclidean distances between successive points of a sample D and b respectively, are measured also the maximum distance between the first point and other point of the sample l. The fractal dimension can be expressed as [24]:

$$KFD = \frac{log(D/b)}{log(l/a)} = \frac{log(m)}{log(m) + log(l/b)} \tag{7}$$

where, $m = D/a$. In this experiment the KFD values of each EEG subband have been calculated and used as EEG features. The kurtosis (K) can be expressed as a measure of how outlier-prone a distribution is. The kurtosis of a distribution is given by [25],

$$K = \frac{E(x-\mu)^4}{\sigma^4} \tag{8}$$

where, μ is mean and σ is standard deviation (STD). The significance of these features have been investigated by KW test.

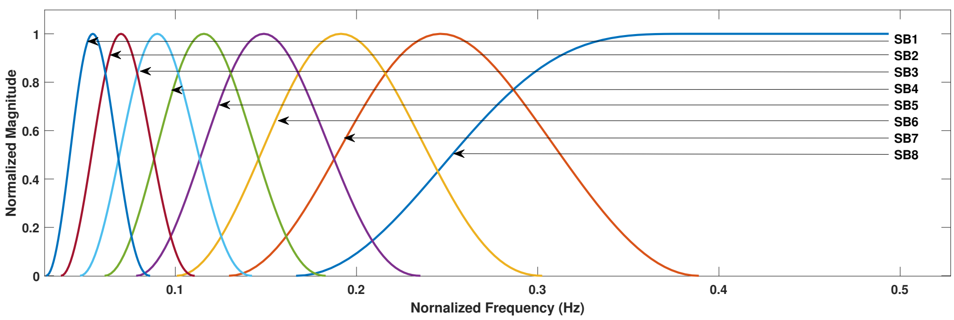

Figure 3. TQWT-based frequency responses starting from the approximate SB to the detailed SBs

2.5. Classification

In present study, to detect the AD from NC using KFD, TsEn, ReEn and K feature sets, we explored various classifiers namely fine-DT, cubic-SVM, cosine-KNN, wide-ANN and EBT. The classifiers, as mentioned earlier, are the most powerful, fastest and popular machine learning algorithms in the biomedical signal processing field. The DT solves the various problems of machine learning by tree representation with less computations for data reprocessing. The SVM is robust classifier which can be utilised in multi-class or binary classification or regression. It works on the principle of maximizing the margin in two different classes. To separate the two classes, an optimal hyper-plane is created as decision surface.

The SVM can effectively and efficiently handle the non-linear data, and it avoids the problems of overfitting while testing [20], [26]. The KNN is a faster algorithm due to no training time requirement. Its performance depends on the value of k. In EBT algorithm, we select multiple subsets of training data randomly. Afterwords, each subset is employed to train the DT. The overall performance is the avarage of all predictions of various DTs. In this study, the parameters of all classifiers are selected optimally by using experimental evaluation. The different performance evaluation parameters, including accuracy (ACC), specificity (SPE), sensitivity (SEN), precision (PPR), F1-score, Mathew's correlation coefficient (MCC), and Cohen's kappa value ($\kappa-$value), are calculated to justify the significance of proposed method [27].

3. RESULTS AND DISCUSSION

In present study, to detect the AD from NC using KFD, TsEn, ReEn and K_u feature sets, we explored various classifiers namely *fine*-DT, *cubic*-SVM, *cosine*-KNN, *Wide*-NN and EBT. In the present study, for the detection of AD patients, TQWT based time-frequency method has been used to overcome the limitations of wavelet and FFT. The TQWT parameters $Q = 1, R = 3$, and $J = 8$ are selected to decompose EEG signals to produce nine SBs. The selected features are calculated from nine SBs. The statistical analysis of extracted feature sets has been performed using the KW test. KW test provides the value of *p* probability. If values of *p* < 0.05, are significant to discriminate the different classes. The *p* probability values for KFD, TsEn, ReEn and K features have shown in Table 1.

Table 1. Summary of *p*-values calculated using KW test for AD vs NC classes in each SB

Subbands	KFD	TsEn	ReEn	K
SB_1	1.01×10^{-33}	3.53×10^{-118}	3.37×10^{-45}	4.62×10^{-14}
SB_2	1.94×10^{-15}	4.44×10^{-122}	9.82×10^{-64}	9.34×10^{-21}
SB_3	9.93×10^{-17}	4.15×10^{-87}	6.58×10^{-42}	8.75×10^{-7}
SB_4	5.29×10^{-15}	5.08×10^{-62}	1.70×10^{-48}	1.23×10^{-5}
SB_5	1.15×10^{-110}	8.03×10^{-29}	7.49×10^{-16}	4.25×10^{-8}
SB_6	1.00×10^{-139}	3.61×10^{-4}	5.55×10^{-24}	1.08×10^{-17}
SB_7	2.01×10^{-143}	4.21×10^{-6}	6.48×10^{-15}	4.49×10^{-11}
SB_8	8.92×10^{-127}	9.43×10^{-8}	5.45×10^{-17}	8.89×10^{-5}
SB_9	1.07×10^{-150}	1.94×10^{-4}	9.02×10^{-14}	3.94×10^{-12}

From Table 1 it is noted that all features are having $p < 0.05$. Hence, all features were selected for further analysis. The five different classifiers, namely *Fine*-DT, *Cubic*-SVM, KNN, *Wide*-ANN, and EBT are trained and tested using the above evaluated feature sets. The model parameters and kernel functions for each classifier have been adopted from various iterations. The ten number of splits in *Fine*-DT are selected. In *Cubic*-SVM, the kernel was chosen as automatic. The parameter values such as k and number of splits are 50, and 10 were selected. The learning rate of 0.1 and the activation function as ReLu have been selected to achieve maximum accuracy. In ANN, the layers and iteration limit were two and 500, respectively. Table 2 demonstrates the classification accuracy obtained from various classifiers for each SB. The EBT performs best out of all five models with a classification accuracy of 96.2% using SB_7 feature sets.

After EBT, the KNN performs better and provides an accuracy of 94.1% for SB_7. The highest accuracy obtained from the DT model is 91.9% for SB_7, and worst is 87% for SB_9. In the case of SVM, higher ACC obtained is 93.8% for SB_7 and lower ACC is 84.8% for SB_9. DT and NN perform poor compared to other classification models. The EBT performs worst for the feature sets from SB_9. Out of nine SBs, the seventh SB have the highest discriminating ability compared to other SBs. The performance evaluation parameters ACC, SEN, SPE, precision, F1-score, MCC, and κ-value for classifiers with SB_7 have presented in Table 3.

Table 2. The classification accuracy (%) for each SB evaluated by variety of classifiers with 10-fold cross validation technique when $Q = 1,\ r = 3$, and $J = 8$

Classifier	SB_1	SB_2	SB_3	SB_4	SB_5	SB_6	SB_7	SB_8	SB_9
Fine-DT	89.3	88.1	89.1	90.5	91.1	91.7	91.9	90.3	87.0
Cubic-SVM	93.7	91.9	93.1	92.8	93.5	93.4	93.8	92.5	84.8
Cosine-KNN	93.1	92.8	92.6	92.5	91.9	92.5	94.1	91.7	83.0
EBT	93.2	91.7	91.4	92.2	93.1	93.1	**96.2**	93.7	85.5
Wide-ANN	92.3	91.7	92.3	92.8	92.9	91.9	91.7	91.6	84.5

Table 3. Performance parameters of classifiers using SB_7 feature sets

Classifier	Kernel	ACC (%)	SEN (%)	SPE (%)	Precision (%)	F1-score (%)	MCC (%)	κ-value (%)
SVM	Cubic	93.80	89.35	96.50	93.24	94.84	86.73	86.64
KNN	Cosine	93.10	86.69	96.75	91.77	94.55	85.86	85.59
EBT	Bagged tree	**96.20**	90.49	97.50	93.48	95.09	87.37	87.28

From Table 3, it is observed that EBT has the highest SEN 90.49% and SPE 97.5%. The worst SEN and SPE noted by DT, i.e. 86.6% and 92.5% respectively. The precision, F1-score, MCC, and κ values for EBT are $93.24\%, 94.84\%, 86.73\%$, and 80.64% respectively.

The comparison of the proposed method with state of the art techniques which have used same EEG datasets have been shown in Table 4. Abásolo *et al.* has developed various entropy based technique to detect the AD from NC from EEG signals and obtained maximum ACC of 90.91% for ApEn and AMI [6], [7], [9], [10]. Escuredo *et al.* proposed a MSE based method to overcome the limitations of ApEn and achieved the ACC of 90.91%. Afterwords, Simons *et al.* used QSE and FuzzyEn to detect AD [8], [11]. The FuzzyEn provided the 86.36% classification ACC. It must be noted that the above mentioned methods used only time domain complexity features. The proposed method achieved the 96.20% ACC with TQWT and EBT from SB_7.

The comparison of proposed method with the recently reported methods which used different EEG datasets have been shown in Table 5. All the methods mentioned in the Table 5 were used wavelet based features to detect the AD from NC. Safi *et al.* used wavelet based HP features and achieved maximum ACC of 95.79% with SVM among all other studies [14]. In the proposed method, EBT classifier has provided promising results in detecting AD patients from NC subjects using the TQWT based features from the seventh SB.

Table 4. Comparison of proposed method with earlier reported methods for same EEG dataset

Reference	Features	Classifier	ACC (%)	SEN (%)	SPE (%)
Abasolo *et al.* [6]	ApEn	Threshold	-	70	100
Abasolo *et al.* [7]	SpEn and SampEn	Threshold	77.27	90.90	63.64
Escurdero *et al.* [8]	MSE	Threshold	90.91	90.91	90.91
Abasolo *et al.* [9]	ApEn and AMI	Threshold	90.91	100	81.82
Simons *et al.* [10]	Quadratic SampEn	Threshold	77.27	-	-
Simons *et al.* [11]	FuzzyEn	Threshold	86.36	90.91	81.82
Puri *et al.* [18]	SpeEn and KC	SVM	95.60	95.20	95.20
Proposed work	TQWT based TsEn, ReEn, KFD, K	EBT	96.20	90.49	97.50

Table 5. Comparison of proposed method with earlier reported methods for same EEG dataset

Ref	Dataset	Features	Classifier	ACC (%)	SEN (%)	SPE (%)
Oltu *et al.* [13]	20 AD, 15 NC	Wavelet Entropy, band power	LDA	78.43	82.35	70.59
Durongbhan *et al.* [16]	8 AD, 20 NC	Wavelet SBs magnitude	KNN	83.32	72.57	87.52
Sharma *et al.* [15]	15 AD, 16 MCI, 13 NC	PSD of wavelet SBs	SVM	87.90	88.00	88.00
Safi and Safi [14]	20 AD, 31 MCI, 35 NC	Wavelet based HP	SVM	95.79	91.93	97.85
Proposed	12 AD, 11 NC	TQWT based TsEn, ReEn, KFD, K	EBT	96.20	90.49	97.50

4. CONCLUSION

The outspread of AD is increased in recent years. The early detection of AD can delay the growth of degeneration of neurons in a brain. Hence cost-effective, accessible techniques to detect AD are urgently

needed. In the present work, we developed a method to detect the AD patients from NC subjects using a novel approach of channel optimization and TQWT based features extraction. Initially, the number of channels are optimized using Shannon entropy to signal energy ratio. The EEG signals from 10 optimized channels were decomposed into nine different SBs. The four different features are extracted from nine SBs to train and test various classification models. The extracted features from SB_7 with EBT produced the highest classification accuracy of 96.20% with ten-fold cross-validation and it outperforms the state of the art methods.

It is essential to take note of that; the informational index is tiny in light of the fact that most datasets are not publicly accessible. Large example size and very different arrangements of information are needed to make this test accessible. Our future work will include the diagnosis of AD patients and general EEG using the latest in-depth study methods.

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